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ORIGINAL ARTICLE

Potential Application of Artificial Neural Network (ANN) Analysis Method on Malaysian Road Crash Data

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ABSTRACT – By allowing the movement of commodities and people, road transportation benefits both nations and people. This provides improved access to work opportunities, educational attainment, recreation, and healthcare, all of which have a direct and indirect influence on people. The influence on road transportation, on the other hand, has a detrimental impact on people's health. When addressing road traffic accidents, it is common known that it has merely become a global pandemic, with over a million people dying on the road each year. Malaysia, as a growing country, has identified road safety as a major issue that must be addressed. Reliable road safety statistics are critical for comprehending, assessing, and monitoring the nature and scope of the road safety problem and its solutions, for setting ambitious but realistic safety targets, for designing and implementing effective road safety policies, and for monitoring their success. Several approaches are presently utilized by road safety researchers to produce road safety indicators. In Malaysia, nearly all decisions made by the country's higher authorities to enhance road safety are based on data supplied by relevant stakeholders. As a result, having the proper application of analysis as well as the trustworthiness of the data itself is critical. This article will give a review of the possible use of the Artificial Neural Network (ANN) Analysis technique on traffic road collision data and what it may provide to assist monitor or forecast road safety issues, specifically in Malaysia. A new era in the field of road accident investigation is being ushered in by the development and application of analytical methodologies, which are creating previously unimaginable situations. Due to the convergence of recent advancements in accident research models and the availability of potentially new sources of traffic data, this paradigm shift has been made possible. The study of road crashes has benefited significantly from the development of more advanced data processing methodologies and frameworks, thus the researchers will able to extract significant conclusions from the study of traffic data thanks to the application of these approaches.

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INTRODUCTION

Road transportation offers advantages both to nations and to the people by enabling movement of goods and people. This enables increased access to job opportunity, education reachability, leisure and healthcare which converts into direct and indirect impact on to the populations. However, the impact on road transportation also brings negative consequence on the health status of the people. This generally comes in the forms of direct impact such as casualties due to road traffic crashes and respiratory illness due to vehicle gas emissions other than indirect effects on health consequences due to lack of physical movement [1].

When discussing road traffic crash, it is already a general knowledge that it has merely become a global pandemic with more than a million people die on the road each year. Malaysia, as a developing country, has identified road safety as a critical issue that requires attention. In Malaysia, road traffic crash falls within five principle causes of death (3.8% of the population, after heart disease, pneumonia, and cerebrovascular disease [4]. With approximately 30 million inhabitants, Malaysia is ranked among the riskiest countries by the three internationally comparable indices measured by number of fatalities per 10,000 registered vehicles, 100,000 populations, and 1 billion VKT (Vehicle Kilometer Travelled) [2].

Access to road safety data is critical for enhancing road safety outcomes, tracking progress, and meeting set road safety targets. Reliable road safety data are critical for comprehending, assessing, and monitoring the nature and scope of the road safety problem and its solutions, for setting ambitious but achievable safety goals, for designing and implementing effective road safety policies, and for measuring their effectiveness. With regards to establishing road safety indicators and indexes, several methods are currently used by road safety researchers around the globe. This paper will

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provide review on the potential application of Artificial Neural Network (ANN) Analysis method on traffic road crash data and what it could offer to help to monitor or predict the road safety situations, particularly in Malaysia.

RELATED WORK

ROAD SAFETY SITUATIONS IN MALAYSIA

In Malaysia, the regulation and investigation of road traffic is stipulated under the 1987 Law 333 Road Transport Act (RTA) 1987 or known as Act 333. With regards to enforcement, the Royal Malaysia Police (RMP) under Ministry of Home Affairs (MHA) and the Road Transport Department (RTD) under Ministry of Transportation (MOT) have adopted the same act to enforce traffic laws. The investigation by the RMP serves as legal purposes grounded by Act 333 covers all level of crash severity; fatal, serious, slight and damage only. Due to the wide range of spectrum covered, it is often the referred source of data for road traffic monitoring and analysis in the country.

Over the past few years, Malaysia has seen people mobility as a vastly increasing trend, both in terms of frequencies and distance travelled. This is nonetheless due to its status of a fast-growing middle-income country by socioeconomic standpoint (based on Gross National Income) [3]. The simple cause and effect are the more exposure on the road tend to contribute higher rate of fatalities among road users. Malaysia experienced an annual increase of 4% in road traffic fatalities in the 1980s in average, increasing to 5% in the 1990s. However, in recent years (2000–2009), the figure increased at a slower rate of 2%, as shown in Figure 1.

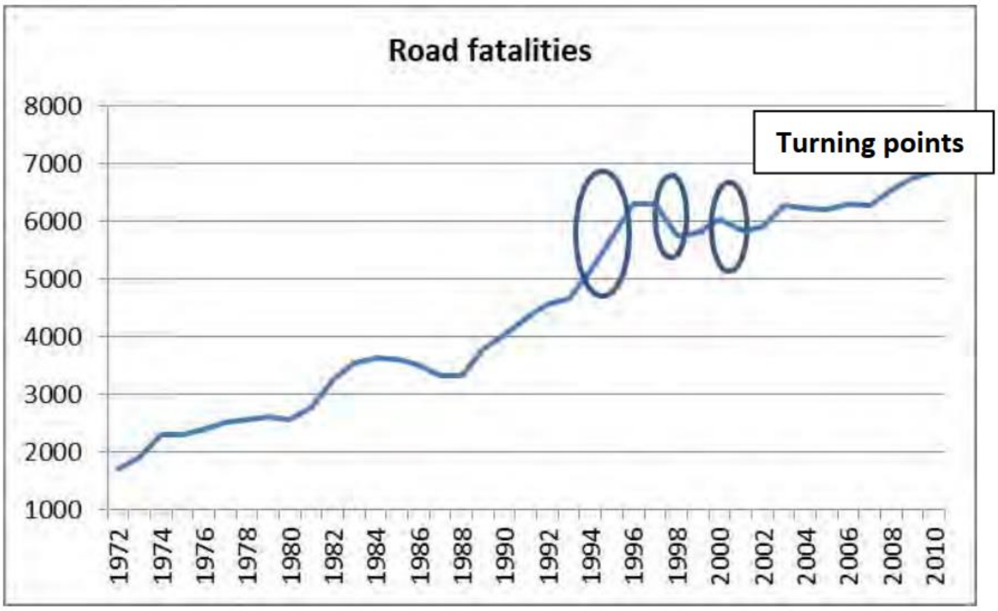


Figure 1. Malaysian Road Fatalities (Source: Rohayu et al., 2012)

Various efforts were put on stage to compensate the death tally. As a matter of fact, efforts and interventions have started as early in 1970’s from the introduction of the first motorcycle lane along Federal Highway to reduce conflict and crashes [5]. to the latest in mandating the use of Child Restraint System (CRS) in year 2020. However, the biggest challenge is that despite efforts being put in to curb the numbers, this epidemic seems to be still happening.

In Malaysia, almost all decisions made by the country's higher authorities to improve road safety are based on data provided by relevant stakeholders. Thus, having the appropriate application of analysis is critical, as is the data's reliability. Errors in this data will result in the incorrect identification of hazards and road segments, the projection of false estimates, and the detection of incorrect parameters, rendering the entire road safety exercise ineffective [5-7].

FATALITY MODELS IN MALAYSIA

Road safety data analysis can provide various inputs on gauging road safety performance. In Malaysia, based on crash data provided by the RMP which is then analyzed by MIROS, three road safety indicators were often used which are ‘Fatality Index by Vehicle Kilometer Travelled’, ‘Fatality Index by 10,000 Vehicles’ and ‘Fatality Index per 1,000,000 Population’. Apart from that, these data are often used to create prediction models of fatalities due to traffic crashes [4].

Various sorts of models are used globally to forecast road fatalities as a result of traffic accidents. This is a critical stage in developing targets for road safety. Essentially, the methods for this type of goal planning can be classified into three categories: model-based, extrapolation- and evidence-based judgmental techniques, as well as aspirational approaches [7]. Several fatality models have been developed for Malaysian road traffic fatalities. These have been incorporated into the country's road safety plans. Among others, Rehan [6] pioneered the field of road traffic fatality modelling in Malaysia, proposing the following model:

$$Death = 0.08193\ (population\ x\ number\ of\ vehicle)^{0.335} \tag{1}$$

However, the increase in road networks by opening of new expressways, together with the increasing number of vehicles have resulted a much lower forecasted figure than actual. Thus, the needs of a revised the model was there. Then, using multivariate time series modelling, fatalities in Malaysia were estimated using linear models based on Poisson distributions, which were later improved by Radin [5], by including additional explanatory variables such as road length and the effect of standardised accident data. Numerous subsequent efforts were made to improve the model over the years, including the use of McCullagh and Nedler's 'quasi-likelihood' method [8]. Radin [5] developed the following exponential model to account for fatalities in Malaysia:

$$Death = 2289\ (e^{0.00007vehicle.population.road})(e^{0.2073system}) \tag{2}$$

The projected fatalities using the above model was based on 'business as usual' or (BAU) approach. Starting from year 2000, the projected fatality figure was established. As a result of this projection, the BAU approach must be modified. As a result, intervention programmes were developed, and the government committed to reducing the forecasted deaths. Later, the reduction target was increased from 30% in 2000 to 50% in 2020.

ARTIFICIAL NEURAL NETWORK (ANN) ANALYSIS FOR ROAD CRASH ANALYSIS

In artificial neural networks modelled after the brain, neuron nodes are connected in a web-like fashion. The human brain contains billions of neurons, which serve as the nervous system's building blocks. Each neuron contains a cell body that is responsible for information processing and transmission to and from the brain. An ANN is made up of hundreds or thousands of processing units connected via nodes. These units include both input and output modules. The neural network attempts to learn about the data presented in order to generate a single output report based on the input units' internal weighting system. By utilising a "transfer function," these elements can accept data from multiple sources and compute an output based on the inputs. Weighted connections connect neurons; data flows through these connections and is scaled appropriately during transmission based on the weights applied during construction (Fig. 2).

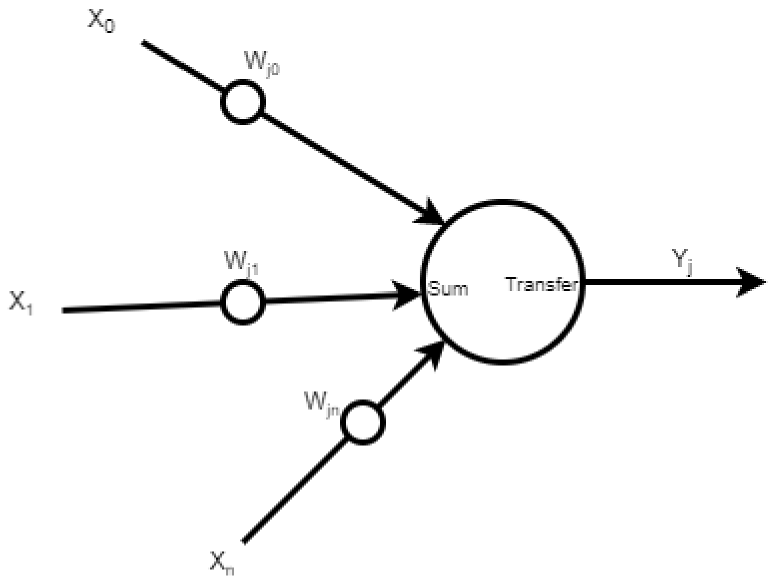


Figure 2. A single processing element in Artificial Neural Network (ANN)

Equations (1) and (2) describe the relationship between neuron j's inputs X_0... X and its output Y. (2). The function is usually non-linear, like a sigmoid.

(Summation) (3)

$$I_j = \sum_{i=0}^{n} W_{ji} X_i$$

(Transfer) $$Y_j = f(I_j) \quad (4)$$

Thus, one neuron's output can influence another's input. Unusable without external communication, some connections take data in from an external source, while others send data back out. Due to the fact that the weights of the connections can be updated over time, the neural network can adapt and possibly "learn." Due to the abstract nature of this concept, neural network practitioners have tended to impose a more rigid structure. A strict rule governs the existence of a connection between two neurons. Thus, the output of each neuron in one layer is fully connected to the output of all neurons in the next layer. This is a typical characteristic of a feedforward network (Fig. 3). Additionally, there is a "learning rule" that controls how and when connection weights are updated. Each neuron in a layer, and frequently the entire network, uses the same formula to compute an output from a set of weighted inputs, resulting in a unified output. Numerous examples of artificial neural networks are feedforward networks, which means that no circular information paths exist; data flows in discrete steps from the input to the output. Recirculation networks, on the other hand, are capable of accomplishing this. When using this approach, it is assumed that all neurons compute their results at the same time, and that the process can be repeated. The learning rule used in neural networks can be classified.

Additionally, the use of neural networks in transportation dates back to the 1990s, when researchers proposed the target subject area of road route design. [8]. The study uses artificial neural networks to design a road route that is effective and ergonomic for human behavior. The artificial neural network method is found to be useful in analyzing a non-linear transport system. Table 1 [9] summarizes data from police investigation reports and categorizes and variables them.

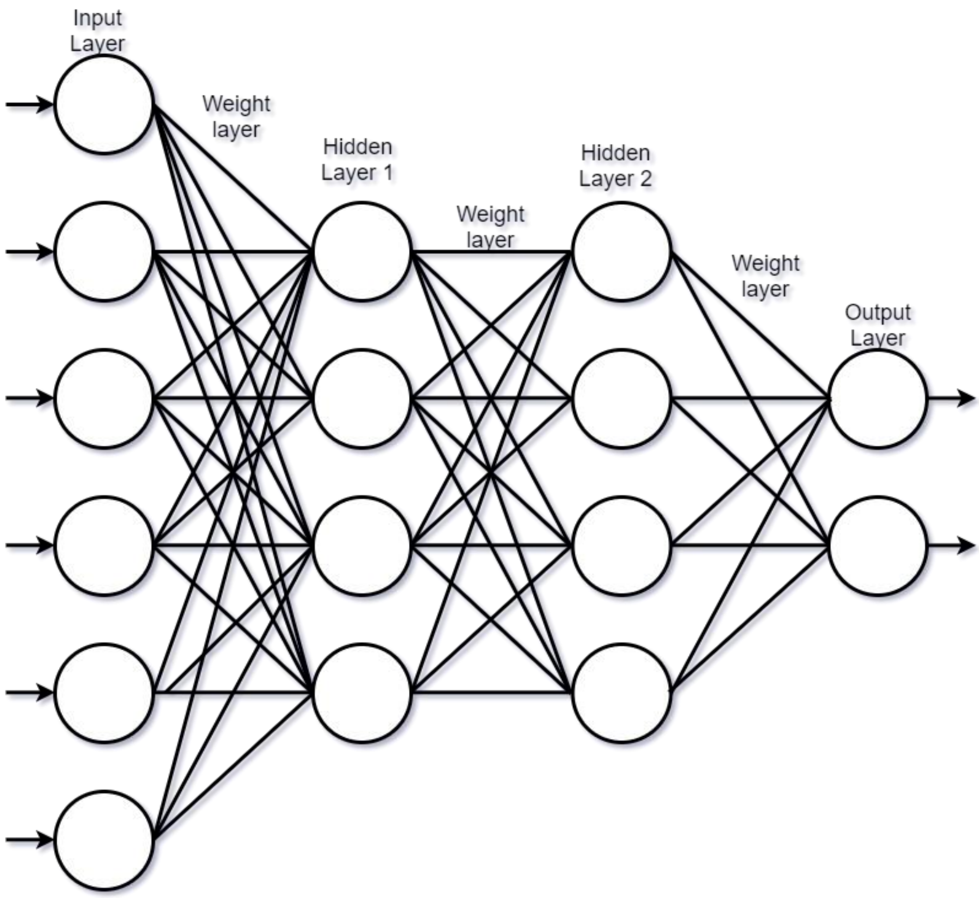


Figure 3. Example of typical ANN model with 2 hidden layers

The committee members summarized their appraisal report for each accident, which was based on the police investigation's findings. The committee unanimously approved the appraisal report, which included a clear statement of all parties' accident liabilities, as well as a detailed explanation of why they were liable. A total liability for all parties is divided into five categories: complete responsibility (i.e., the party required to accept full responsibility for the accident's cause), significant responsibility, equal responsibility, minor responsibility, and no responsibility. Complete and total responsibility is the most serious of the categories. According to the five levels of responsibility described in this paper, appraisal liabilities are denoted by the letter y, and their values are denoted by the numbers 1, 2, 3, 4, and 5. Additionally, the study summarized the various types of collisions involving two cars that occurred, as shown in Table 2 [9].

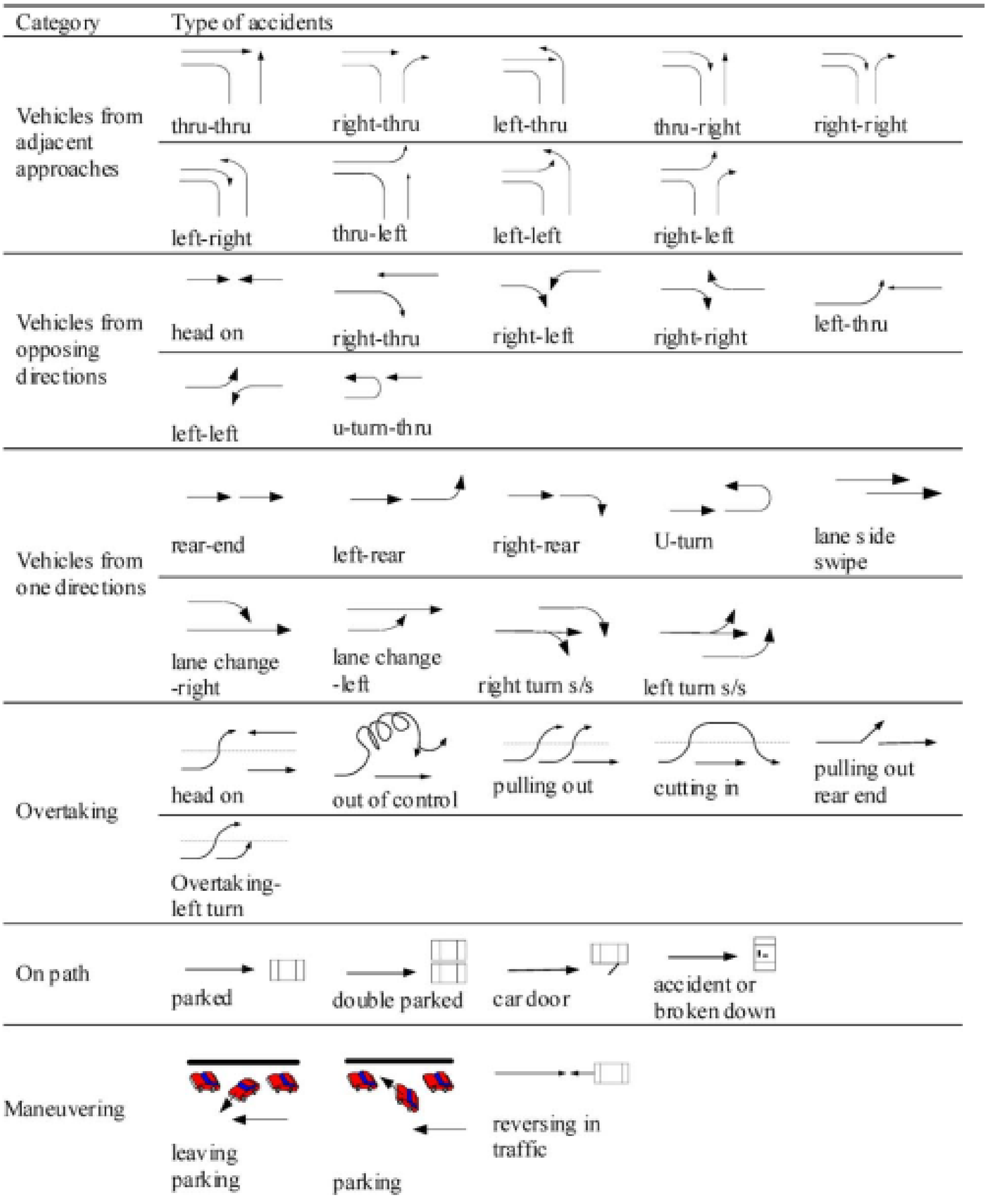
Table 1. A part of the summarized investigation report information by police in Taiwan [9]

Category	**Information**	**Coding**	**Description**	**Variable**
Background	Date	Character	Month/date/year	X_1
	Time	Character	Hour/minutes	X_2
	Type of Road	Categorical	1, national freeway; 2, provincial highway; 3, county highway; 4, rural highway; 5, street	X_3
	Location	Categorical	1, straight road; 2, curved road; 3, signalized intersection; 4, flashlight intersection; 5, not signalized intersection	X_4
	Major and Minor Street	Categorical	1, straight road; 2, curved road; 3, signalized intersection; 4, flashlight intersection; 5, not signalized intersection	X_5
	Lane Located	Categorical	1, inner lane; 2, outer lane; 3, middle lane; 4, slow lane; 5, one-way street	X_6
	Daylight or darkness	Categorical	1, daylight; 2, night with illumination; 3, night without illumination	X_7
	Weather condition	Categorical	0, clear; 1, rainy or cloudy	X_8
	Flash signal	Categorical	1, red light; 2, yellow light; 3, no flash signal	X_9
	Speed limit	Continuous	km/h	X_{10}
Demographic	Gender of the driver	Categorical	1, male; 2, female	X_{11}
	Age of the driver	Integer	Years	X_{12}
	Education	Categorical	1, university; 2, college; 3, high school; 4, high vocational school; 5, junior high school; 6, elementary school; 7, kindergarten	X_{13}
	Type of vehicle	Categorical	1, passenger car; 2, business car; 3, light truck; 4, truck; 5, bus	X_{14}
	Length of vehicle	Continuous	Meter	X_{15}
Violations	Licensing	Categorical	1, yes; 2, no (above licensing age);	X_{16}

			3, no (under licensing age)	
	Speeding	Categorical	1, seriously speeding (over 20 km/h); 2, speeding; 3, no	X_{17}
	Invasion	Categorical	1, invasion to opposing direction; 2, moving backward; 3, no violation; 4, not clear; 5, not follow the signal or markings	X_{18}
	Alcoholic use	Categorical	1, yes (>0.55 mg/l); 2, yes (0.25–0.55 mg/l); 3, yes (<0.25 mg/l); 4, no	X_{19}
Behaviors	Movement	Categorical	1, forward; 2, right turn; 3, left turn; 4, u turn; 5, stop; 6, backward	X_{20}
	Direction	Categorical	1, east to west; 2, west to east; 3, south to north; 4, north to south	X_{21}
	Lane change	Categorical	0, none; 1, yes; 2, overtaking	X_{22}
	Foresight of the accident	Categorical	0, none; 1, yes; 2, not clear	X_{23}
	Foresight distance	Continuous	Meter	X_{24}
	Reaction	Categorical	0, none; 1, flash; 2, flash right; 3, flash left; 4, lane change; 5, reverse; 6, detour; 7, horn; 8, flash light; 9, decelerate; 10, stop; 11, pass; 12, not clear; 13, escape	X_{25}
	Braking	Categorical	0, none; 1, brake before crash; 2, brake after crash	X_{26}

The category demonstrated a very promising relationship and can be used as a reference for assessing the likelihood of road crashes. A nearly identical analysis was conducted in a study on the factors affecting the occurrence and severity of rear-end collisions in Abu Dhabi, is shown in Table 3. This information is necessary in order to obtain accurate hidden layers and thus accurate output for ANN [10].

Table 2. Categories for the type of accident by two cars



Category	Type of accidents				
Vehicles from adjacent approaches	thru-thru	right-thru	left-thru	thru-right	right-right
	left-right	thru-left	left-left	right-left	
Vehicles from opposing directions	head on	right-thru	right-left	right-right	left-thru
	left-left	u-turn-thru			
Vehicles from one directions	rear-end	left-rear	right-rear	U-turn	lane side swipe
	lane change -right	lane change -left	right turn s/s	left turn s/s	
Overtaking	head on	out of control	pulling out	cutting in	pulling out rear end
	Overtaking-left turn				
On path	parked	double parked	car door	accident or broken down	
Maneuvering	leaving parking	parking	reversing in traffic		

Table 3. Factors affecting the occurrence and severity of rear-end crashes in Abu Dhabi

Driver variables		Rear-end crashes		Other crashes	
		Number	Percentage	Number	Percentage
Gender	Male	1773	93%	8127	90%
	female	133	7%	951	10%
Age	(18-25)	535	28%	2466	28%
	(26-35)	694	37%	3300	37%
	(36-45)	370	20%	1719	19%
	> 45	288	15%	1350	15%
Nationality	Locals	629	33%	2881	32%
	Arabian	447	23%	2195	24%
	Asian	787	41%	3757	41%
	Other	44	2%	245	3%
Education level	Low	1745	92%	5040	56%
	High	159	8%	4006	44%
Number years of experience	(0-4)	455	24%	2451	27%
	(5-9)	718	37%	3178	34%
	(10-14)	289	15%	1195	13%
	≥ 15	265	14%	1213	13%
	Unknown	208	11%	1188	13%

The characteristics and primary causes of rear-end collisions in Abu Dhabi are summarised in Table 4. According to road characteristics, the majority of severe rear-end collisions occur on rural roads (61%) and on non-intersection segments (91%). According to the data, rear-end collisions occur more frequently as road speed limits are increased. Additionally, rear-end collisions occur more frequently during the morning and evening rush hours. Because the majority of roads in Abu Dhabi are well lit and the weather is almost always dry, the results indicated that the majority of rear-end collisions occurred in adequate light, on a dry surface, and in clear weather. When it comes to the primary causes of rear-end collisions, tailgating is the most prevalent (approximately 54%), followed by abrupt lane changes and speeding. According to one study, modelling crashes based on their severity as ANN output, which is typically described as light injuries (LIN), severe injuries (SIN), and fatalities (FAT) [11]. As illustrated in Figure 4, the study proposed an information flow schematic chart embedded with two ANNs [11].

Table 4. Characteristics and main causes of rear-end crashes occurred in Abu Dhabi

(Road/vehicle/crash/ environments) Variables		Category	Percentage
Road features	Road Type	Rural	61%
		Urban	39%
	Speed Limit	40 kph	7%
		60 kph	24%
		80 kph	19%
		100 kph	20%
		≥ 120 kph	30%
	Intersection-related	At intersections	6%
		Non-intersection segments	92%
	Number of lanes	≤ 2 lanes	31%
		3 lanes	28%
		≥ 4 lanes	26%
	Surrounding land use	Residential/commercial	31%
		Public services	15%
		Others	54%
Vehicle feature	Vehicle type	Passenger cars	80%
		Heavy vehicle	17%
Environmental	Light condition	Enough light (day time/night with high illumination)	94%
		Other (night with low or without illumination)	6%
	Weather	Clear	96%
		Unclear	4%
	Surface road condition	Dry	97%
		Other (wet/sand)	3%
	Day Time	Morning	28%
		at Noon	26%
		After noon	12%
		Evening	34%
	Day of week	Weekend days	23%
		Working days	77%
Crash Feature	Crash Causes	Sudden lane change	14%
		Speeding	10%
		Alcohol	5%
		Sleepy	1%
		Tailgating	54%
		Reckless	7%
		Dangerous Road Access	4%
		Others	5%

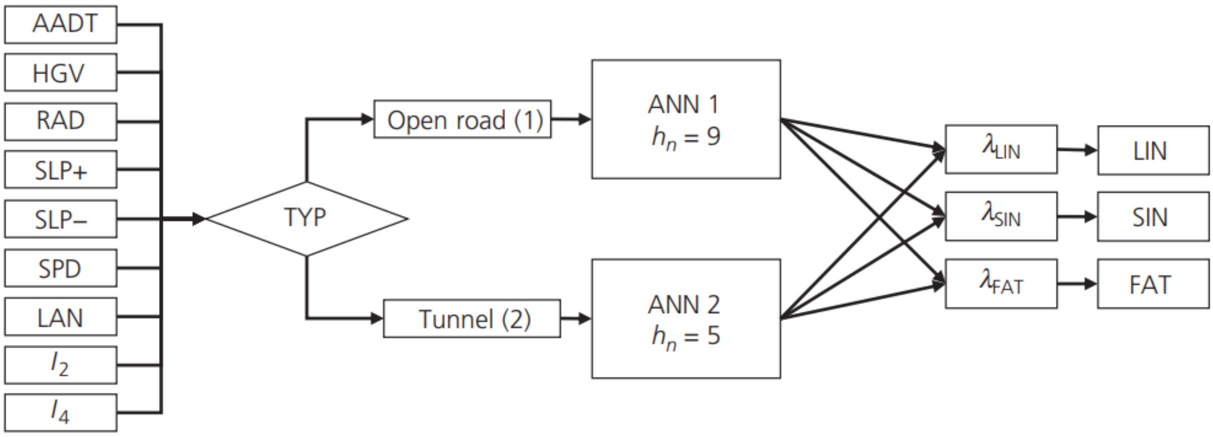


Figure 4. Information flow schematic chart

Additionally, several studies have compared ANN models' performance to that of alternative techniques. To forecast the number of accidents, an ANN model was constructed and proven to be a more accurate alternative to a negative binomial regression model. Three types of modelling techniques were investigated: Bayesian artificial neural networks, (backpropagation) artificial neural networks, and negative binomial regression. According to the findings of the study, they discovered that both the ANN and Bayesian ANN models outperformed negative binomial regression when it came to predicting vehicle accidents. After conducting a research study on road traffic accidents in Sudan, it was discovered that both ANN and Bayesian Neural Networks make close comparable predictions [11].

POSSIBLE APPLICATION OF MACHINE LEARNING FOR ROAD CRASHES ANALYSIS IN MALAYSIA

Passenger automobiles account for 44.8% of total traffic in Malaysia, while registered motorcycles account for 47.0%. Malaysia's road network totals 124,656 kilometres, with 1.3 percent being tolled expressways, 13.6% being primary roads, 43.9% being secondary roads, 34.8% being local roads, and 6.4% being minor roads. Numerous studies have examined the elements that contribute to road traffic accidents in a specific region in Batu Pahat, Johor, and have found that the highest accident rates occur at crossroads and T/Y junctions [15, 16, 17].

Technically, it is demonstrated that, for the purposes of machine learning, specifically ANN, the type of road could be the primary input in determining the likelihood, severity, and number of crashes [16]. According to previous researchers' recommendations, it is necessary to obtain the necessary data from the Royal Malaysian Police as a first milestone, as police are typically the first teams to reach the accident occurrence perimeter. With MIROS's assistance, the data acquired can be increased in accuracy, as the report will be in an easy-to-read format similar to a check list, with brief and concise observation reports, and can also be uploaded to a cloud server. Due to the fact that Artificial Neural Network analysis requires precise and specific input and output, it is necessary to facilitate in-depth discussions among stakeholders. Numerous researchers have discussed road traffic accident topics in Malaysia and various conditions associated with road safety hazards [18-24], and this information can be used to improve the accuracy of ANN analysis.

CONCLUSION

The invention and implementation of analytical tools has heralded the beginning of a new age in the field of road accident analysis, one that has never been seen before. A number of recent advancements in accident research models, as well as the availability of promising new sources of traffic data, have all contributed to the rapid pace of this evolution in recent years. The introduction of more appropriate and advanced data processing techniques and frameworks has had a significant positive impact on the field of accident investigation. By utilising these techniques (Artificial Neural Network), the researchers are able to derive statistically significant judgments from the analysis of traffic data collected. As research into road accident data analysis progresses, accident investigators must continue to investigate fundamental methodological issues and push the technological envelope in order to stay ahead of the curve. The study covers the sources of road accident data, the strategies for analysing the data, frameworks for predicting traffic accidents, and the management of contributing elements. It is expected that simpler models outperform more complex frameworks on occasion, and advanced techniques have a lot of advantages and disadvantages. Overall, all modelling methods lead to the conclusion that the objectives of the data analysis take precedence over the techniques employed.

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